A Novel Comparison Approach for Tropical Cyclone Satellite Images Using Angle Features

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Abstract

Conventionally, the identification of Tropical Cyclones (TCs) has been highly dependent on subjective human judgment applied to vast amounts of data extracted from satellite images. The most popular approach to comparing two given TCs is to measure the distance between various contour points of the TC extracted from a satellite image. However, this measure has a very high computational cost as it involves point-to-point calculations. In this paper we present a novel approach to TC comparison that is based on a TC's typical spiral shapes. Given two sets of contour points, one for each tropical cyclone, we adjust the similarity of two shapes using angle features found among the successive contour edge points. The adoption of a time warping approach results in a fast and accurate comparison. Implementation and evaluation makes use of a two-layer prototype. Experimental results show that our approach performs better than conventional methods such as the Hausdorff distance measure.

Keywords

Image Comparison, Active Contour point, Distance Measure, Tropical Cyclone, Time Warping, Angle Features

1. Introduction

Tropical cyclones (TCs), including extra-tropical cyclones, typhoons and hurricanes, are a regular, global threat to human lives and property. Obviously, the development of a method for their early identification would allow more time for endangered communities to take suitable precautions. The most effective current approach to forecasting meteorological phenomena such as rainstorms and windstorms is satellite image interpretation. One such approach is the Dvorak technique (Dvorak 1973; 1975), an effective, widely accepted method for identifying and interpreting TCs in satellite images. In Dvorak's theory, tropical cyclones go through a life cyclone that allows them to be classified by their appearance. Problematically, however, cloud patterns exhibit considerable variation and there currently exist no scene analysis techniques that would allow the efficient isolation and extraction of cloud systems from satellite images. Consequently, research into tropical cyclone pattern matching using Dvorak analysis has relied on subjective human justification.

The shapes and features of atmospheric systems as observed in remotely sensed satellite imagery are inherently ambiguous. This results in a certain degree of ambiguity or fuzziness in the processing of images. Most works on the extraction of distinguishable TC features have applied segmentation techniques. Hossain *et. al.* (1999) proposed a reinforcement learning method for adaptively segmenting and extracting TC patterns and features. Combining improved edge detection methods and a region growing method, it denoises using an approximate continuous wavelet transform. Lee and Liu (2000a; 2001) have presented an EGDLM system which automates the satellite interpretation process and provides an objective analysis of tropical cyclones. The system integrates neural dynamics and the contour extraction of TC patterns with a snake model. Lee and Liu (2000b; 2002) have also exploited the chaotic features of neural oscillators, noting their exceptional object segmentation capabilities. Where TCs had formed a distinct eye, subsequent results obtained from the reconnaissance showed a deviation within a few kilometers of the actual eye location. These results indicate that this approach would be of value in improving our use of satellite imagery to identify TCs, and to track and predict their trajectories.

All of above Contour-based approaches, however, incur very high computational costs and are not sufficiently precise in terms of either prediction or comparison. In this paper then, we propose a comparison algorithm, angle feature matching, which is novel in that it makes use of the distinctive spiral features of the TC. As it is very difficult to define cyclones and to directly compare their shapes, we adopt an approximation method that compares pairs of corresponding angles formed by three adjacent contour points from each cyclone. We choose to measure these angles because they control the cyclone's shape. We extract the active contour points of the cyclones using the popular snake model (Seo and Lee 2003) and determine the distance between two sets of angles using a time warping algorithm (Yaniv and Burshtein 2003). To implement our idea, we have designed a two-layer prototype and have evaluated its performance against other, conventional methods. The results show that our approach is faster and more accurate.

The rest of the paper is organized as follows. Section 2 describes the system architecture and the function of each layer. Section 3 provides details both of the angle feature matching model using a time warping distance measure and of how to define the similarity between angles. Section 4 provides experimental results that show the superiority of our approach over other algorithms. Section 5 concludes the paper and presents future work.

2. System Architecture

To implement our proposed tropical cyclone satellite image matching approach, we designed a two-layer prototype which includes an extraction module and a matching module, as shown in Figure 1. The extraction module is tasked with picking up, from an input satellite image in which there is at least one clear cyclone, the dominant points depicting the contours of a TC. The module then selects the contour points of each image and from them calculates a set of angles for comparison. Using these angles, the matching module applies a series of comparison algorithms to retrieve the best-matched image from the template set. Details of the matching process will be discussed in Section 3.

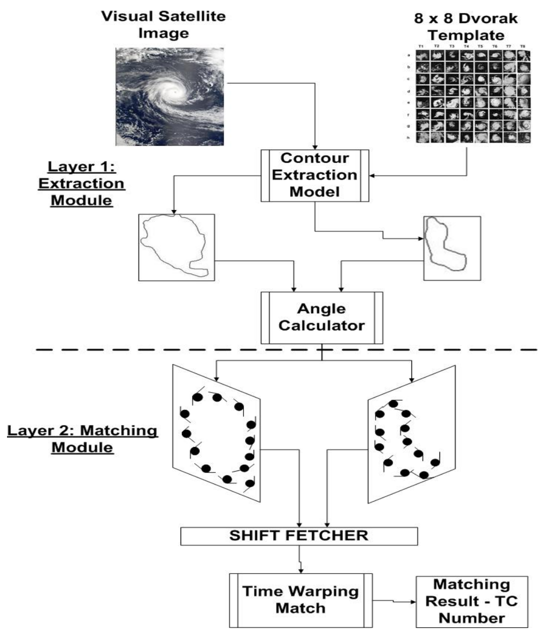

Figure.1. System architecture of a two-layer prototype

The creation of an efficient pattern extraction scheme has been a major challenge in automatic satellite interpretation work (Smith and Stotts 2003). In this paper, as a pre-processing step towards tropical cyclone recognition, we extract patterns and detect contours using the Active Contour or Snake model. The main advantage of the Snake model is that, because it allows for the use of an initial contour estimation, it can overcome several photometric abnormalities such as gaps hidden in contours, or edge points arising from noise and texture. In (Lee and Liu 2001), we proposed an elastic, active contour model. The formulation is given as follows:

$$E_{snake} = \int_0^l E_{int} + E_{ext} ds = \int_0^l \alpha(s)|u_s(s)|^2 + \beta(s)|u_{ss}(s)|^2 + P(u(s)) ds \quad (1)$$

where $u(s)=(x(s), y(s))$ is the snake curve and s is the arc length of the curve. The parameters of elasticity α and β control the smoothness of the snake curve. $P(x, y)$ is associated force, which in general is defined in terms of a gradient module of the image convoluted with the Gaussian function:

$$P(s, y)d(x, y), P(x, y) = -e^{d(x,y)^2} \quad (2)$$

where $d(x, y)$ denotes the distance between this pixel (x, y) and its closed edge point. The snake is moved by potential forces and it tries to fall into a valley as if it were under the effect of gravity.

We set as our goal in the first layer, the extraction module, the comparison of an input satellite image with the Dvorak templates. Thus the snake extraction process is applied not only on the input image, but also on the Dvorak templates. When there is more than one tropical cyclone in the satellite image, we select only the dominant cyclone, that is, the one with the largest area. This is done using a fast algorithm called sequential neighbor checking, which proceeds by first checking a single pixel within the tropical cyclone, then checking its neighbors and each neighbor's neighbors to see whether they also belong to the designated tropical cyclone. This allows every pixel within the same cluster of the tropical cyclone to be correctly examined. For example, Figure 2 gives the clustered result for 2002's Typhoon Dina. Figure 3 provides the pseudo-code for this algorithm.

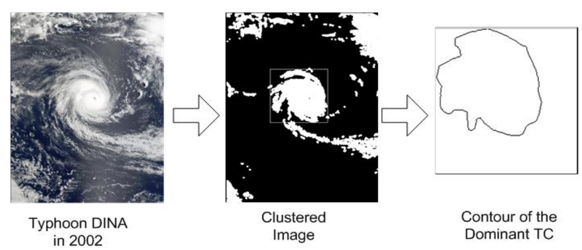

Figure.2. Clustered result for Typhoon Dina in 2002

```
Convert the image into Binary format: BI
Procedure CheckNeighbor (x,y)
1. For each pixel P1 (x1, y1) within BI
2.    If gradient of P1 is white
3.       Set P1 to black
4.       For each right (Up or Down) neighbor P2 (x2, y2) of P1
5.          If gradient of P2 is white
6.             CheckNeighbor (x2, y2)
            End If
         End For
7.       For each left (Up or Down) neighbor P3 (x3, y3) of P1
8.          If gradient of P3 is white
9.             CheckNeighbor (x3, y3)
            End If
         End For
      End If
   End For
End Procedure CheckNeighbor (x, y)
```

Figure.3. Procedure to find dominant tropical cyclone

In the second layer, the matching module, we propose an angle feature matching model which integrates the time warping technique in order to approximate the similarity of two given tropical cyclone contours. The matching module also proposes a simulated cyclone eye location algorithm for calculating the different weights for each angle formed among the contour points. After that, the shift fetcher works as a rotator, comparing two cyclone contours from two input images in all possible offsets.

3. Angle Feature Matching Model

3.1 A weight calculation algorithm

One of the most characteristic features of the appearance of a tropical cyclone is its spiral shape. Another is the contour points extracted from the satellite image. It has proven very difficult to detect the eye of a tropical cyclone using image processing techniques, as the location of the cyclone eye is related to many other factors such as intensity, speed, and acreage. We try to find a "locational eye" for a tropical cyclone. Here, to detect the locational centroid O, we first introduce the definition of pixel distance. For every pixel P within the area bounded by the tropical cyclone contour, if all the neighbors (pixels P+1 in Figure 4) have the same value, the pixel distance of P is set to 1. Accordingly, if the pixels P+1 to P+n all have the same gradient value, the pixel distance of P is set to n. As the locational centroid, we choose the pixel which has the largest pixel distance. The concept of the pixel distance is illustrated in Figure 4.

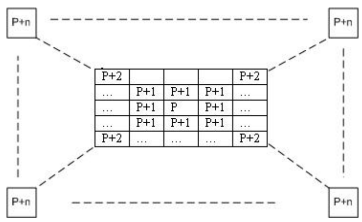

Figure.4. Concept of the pixel distance

In this way, for an extracted contour, we find the locational centroid O(x, y) which contains the largest number of pixel points within the contour with a radius R, as shown in Figure 5.

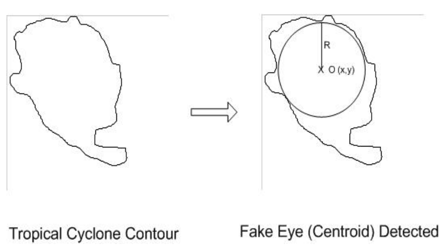

Figure.5. Result of Locational Eye (Centroid) detected

After confirming the locational eye *O(x,y)*, we start the critical task of assigning weights to each point on the contour. Conceptually, points which are nearer to the locational eye *O(x,y)* should have a higher weight, as their influence on the shape, intensity, or other properties of the tropical cyclone will be greater. Based on this, we designed the following algorithm to determine the weight according to the individual distance between the locational eye and those points. As a result, we can use a set of feature vectors to describe the spiral feature of a tropical cyclone:

$$T = \{n_1, n_2, \ldots n_i\}, \quad n_i = [x, y, w] \tag{3}$$

where x and y are coordinates for each contour point and w is the corresponding weight.

3.2 An angle feature matching model

There has recently been considerable research in the area of image comparison: in color histograms (Kim, Kim and Jang 1999), motion vectors (Saengow, Thipakorn and Cochran 2000), contour measures (Kiran and Bora 2003), and so on. In (Feng and Liu 2004), we proposed a modified Hausdorff distance measure (Dubuisson and Jain 1994) for use in the matching of significance-based points in TC satellite images. As noted, the distinctive spiral shape of the TC marks it as a high-potential area of research into image matching through shape comparison, however, this spiral feature is difficult to describe visually. In this work, we approximate the shape features using the angles of every third adjacent contour point by forming a set of sequential angles for each satellite image to be compared. Figure 6 gives an example of the relationships between the angle and three adjacent contour points, where, θ is derived from

$$\theta = \arccos(\sqrt{(|AC|^2 - |BC|^2 - |AB|^2)/(2*|BC|*|AB|)}) \tag{4}$$

and $0 \leq \theta \leq \pi$, as we only consider the internal angle formed by points A, B and C.

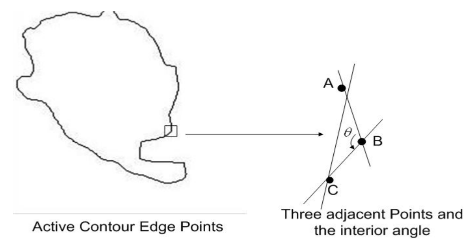

Figure.6. An angle and three contour points.

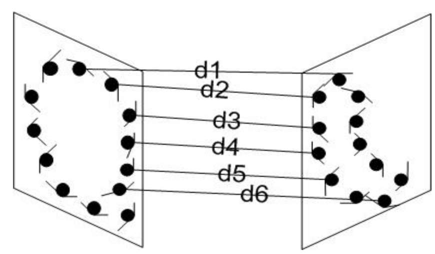

Figure.7. Set of angles for each TC (each **BLACK** node represents an angle formed in Figure 6)

Here we can modify the feature vector for the tropical cyclone from equation 3 into the following format:

$$T = \{n_1, n_2, \ldots n_i\}, \quad n_i = [\theta, w] \tag{5}$$

In this way, for two input tropical cyclone satellite images, we have two sets of angles with different numbers, as shown in Figure 7. The major challenge in this research is to find an efficient and effective approach for calculating the similarity of two sets or for finding the relationships between different distances/differences (d_n) for every corresponding pair of nodes in Figure 8.

In general, the number of angles in two sets usually differs, which makes it critical to use an efficient algorithm when comparing these two sets. In order to allow the shape of two cyclones to be approximately compared synchronously, the angles of each set should be kept in sequence. Instead of directly calculating the distance of every pair of two angles from one set to another, in this paper we adopt the time warping concept (Rath and Manmatha, 2003) as it provides an accurate algorithm for the comparison of two sequences of different lengths. The idea is given as follows.

Given two angle sets, S and Q of lengths n and m, as well as the corresponding weights respectively,

$S=<s_1w_1, s_2w_2, \ldots, s_{n-1}w_{n-1}, s_nw_n> \quad (0 \leq s_n \leq \pi)$

$Q=<q_1w_1, q_2w_2, \ldots, q_{m-1}w_{m-1}, q_mw_m> (0 \leq q_m \leq \pi)$

where s_n and q_m are sets of angles formed by equation 3 for two input tropical cyclones, we can develop an m-by-n grid, as illustrated in Figure 8. Each grid element, (i, j), represents an alignment between angle s_i and q_i. A warping path W is a sequence of grid elements that define an alignment between S and Q.

$$W=(i_1,j_1), (i_2,j_2), \ldots, (i_p, j_p) \quad max(n,m) \leq p<m+n-1 \qquad (6)$$

where (i_p, j_p) corresponds to the p^{th} grid element in the warping path.

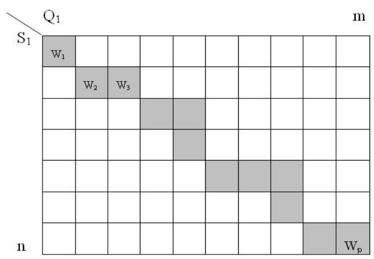

Figure.8. A warping path in an m-by-n grid

After aligning the sequences S and Q, their similarity can be measured by the cumulative distance of the warping path between them. Each element in the warping path is associated with a distance $d(i_k, j_k) = | s_{ik}w_{ik} - q_{jk}w_{jk}|$. Thus the cumulative distance of a warping path is defined as

$$D_c(W) = \sum_{k=1}^{p} d(i_k, j_k) \qquad (7)$$

Many warping paths are possible. We can choose an optimal warping path such that its cumulative distance D_c is the minimum. The corresponding distance is defined as D_{tw}:

$$D_{tw}(S,Q) = \min_{\forall W}\{D_c(W)\} \qquad (8)$$

It would be computationally expensive to search through every warping path, so we propose to find the optimal warping path using a dynamic programming approach (Yi, Jagadish and Faloutsos, 1998). This approach is based on a recurrence formula that defines the cumulative distance, γ (i, j), between angle s_i and q_j, where,

$$\gamma(i,j) = d(i,j) + \min\{\gamma(i-1,j), \gamma(i,i-1), \gamma(i-1,j-1)\} \qquad (9)$$

By adopting equations 7, 8 and 9, we can construct a cumulative distance matrix as shown in Figure 9. This matrix represents such an algorithm using angle sequences Q = {7/8π, 3/4π, 6/7π, 1/2π} and S = {2/3π, 4/5π, 1/3π, 6/7π, 5/8π, 8/9π}. Each value in the cell represents the cumulative distance $\gamma(i, j)$ of that cell, and it is supposed that all weights w_i for the angles are set to 1.0 equally.

S \ Q	7/8π	3/4π	6/7π	1/2π
2/3π	0.205π	0.285π	0.472π	0.302π
4/5π	0.28π	0.255π	0.312π	0.602π
1/3π	0.825π	0.675π	0.782π	0.482π
6/7π	0.843π	0.782π	0.675π	0.839π
5/8π	1.093π	0.907π	0.907π	0.8π
8/9π	1.108π	1.047π	0.94π	1.19π

Figure.9. A cumulative distance matrix for angle sequences Q and S.

After filling up the table, the optimal warping path can be found by tracing backward from the lower right corner towards the upper left corner. At each cell, we choose the previous cell that neighboring cell having the minimum cumulative distance. In this way, 1.19π in the bottom right corner cell can be regarded as the distance of angle sequence S and Q, and is marked as *minDis (S, Q)*.

In certain cases, after self-rotating the input tropical cyclone image by a number of degrees, the contour may provide a better match with the target tropical cyclone image. This means that we should do the comparison more than once. Where there are two angle feature sets, the functional equivalent of rotating the contour is obtained if the element in the angle sequence is shifted once to the left or right. A Shift Fetcher, shown in Figure 1, is designed to repeatedly shift the sequence of S (or Q) and calculates a new cumulative distance matrix like the one in Figure 10. For example, sequence S = {2/3π, 4/5π, 1/3π, 6/7π, 5/8π, 8/9π} will be S_1= {4/5π, 1/3π, 6/7π, 5/8π, 8/9π, 2/3π} after shifting one position to the left. Then we have a new cumulative distance matrix for Q and S_1 and a new $minDis_1(Q, S_1)$. After a loop of shifting all elements of one sequence, from each shift we select the smallest one of $minDis_n(Q,S_n)$ as the final distance of Q and S, as shown in Equation 10:

$$Dis(Q,S) = \min(mindis_1(Q,S_1), mindis_2(Q,S_2), \ldots, mindis_n(Q,S_n)) \qquad (10)$$

4. Experimental Results

To evaluate the efficiency and the effectiveness of our proposed approach, we carried out a set of experiments in which a most-like Dvorak template image is retrieved using a tropical cyclone satellite image as input. The experiments make use of a total of 64 Dvorak template images and 40 satellite images collected from an official U.S. Navy web site (http://www.nrlmry.navy.mil/). Along with the time warping distance approach, for these comparisons we also used two of our previous research works, a modified Hausdorff distance measure (Feng and Liu 2004) and an elastic matching model (Lee and Liu 2001). We have designed the interface of an integrated system that first extracts active contour points from each input satellite image, after which a most-like Dvorak template image is matched using the above three algorithms. Figure 10 shows the experimental results for these three typical algorithms applied to the same input satellite image. In this part, to illustrate the success of our approach, we will discuss the experimental results from the point of view of accuracy and computational cost.

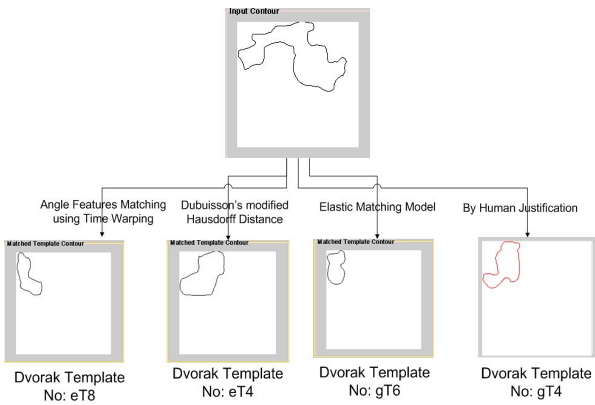

Figure.10. Matching results for three approaches respectively

It is quite difficult to tell how much a retrieved Dvorak template contour is similar to the input one. Mostly, this matter is judged, subjectively and imprecisely, with the human eye. In Figure 10, besides the retrieved results of our proposed approach and two literature approaches, we also give the retrieved result gT4 by human visual justification. Visually we can consider that eT8 and gT4 in Figure 10 are more alike with the input contour than the other two. But due to the subjectivity of human visual justification, such comparison is not convincing and not scientific.

Nevertheless, it is obvious that all data to be processed in the contour matching module are sets of contour points. To calculate the accuracy of the matched contour (namely, B) against the input contour (namely, A), we have designed a Grid Scan method that scales and transforms two sets of contour points into a similar position and size, by putting their "locational eyes" in the center of the image. First, we divide A and B into N x N blocks where N is a predefined number, as shown in Figure 11 below.

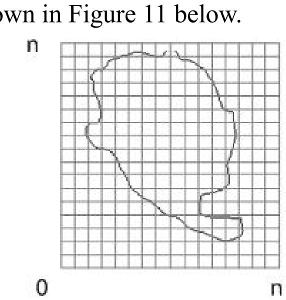

Figure.11. N x N block grid segmentation for a contour

After that we check each block with the same coordinates in A and B to see whether the block contains a contour point. The following equation illustrates the basis of this type of comparison:

$$Accuracy = \sum_{i \in N \times N} (B_i \otimes A_i) \Big/ \sum_{i \in N \times N} A_i \qquad (11)$$

where symbol $\otimes$ denotes the i_{th} block in A and in B, both having an active contour point. Details of the procedure of this comparison are listed in Figure 12 as follows:

```
Count = 0;
Procedure CalculateAccuracy (A, B)
1. Rotate the contour A or B, making them matched best
2. Divide A and B into N x N blocks
3. Scan the blocks, two sequences are achieved as:
        SA = { <a1, p1>, <a2, p2>, ..., <an, pn>}
        SB = { <b1, q1>, <b2, q2>, ..., <bn, qn>}
4. For each point ai
        If pi and qi both contain contour points
            Count ++
        End If
   End For
5. Accuracy = Count / No. of Contour Points in A
```

Figure.12. Procedure for finding the matching accuracy

Using above algorithm, result shown in Table 1 indicates that although gT4 is very similar with the input contour, its calculated accuracy is 10% less than eT8. We are not going to disaffirm human visual justification, but as it is highly dependent on the subjectivity, we won't consider it during our following experiments.

Table 1: Retrieved accuracy for the results in Figure 10

	eT8	**eT4**	**gT6**	**gT4**
Accuracy	72.41%	53.12%	48.7%	62.86%

The experimental results given in Table 2 indicate that the time warping distance measure is more accurate than the other two methods, 79.74% against 74.32% and 63.22% on average, using 40 collected satellite images.

Table 2: Three algorithms compared: Average accuracy (%)

	Elastic Matching Model	Weighted Hausdorff Distance	Time Warping Distance
Accuracy (averaged)	63.22%	74.32%	79.74%

We also assessed the computational cost of each algorithm using a computer with 2.26 GHz Intel Pentium CPU and 512 RAM. All other windows applications were shut down to ensure the most precise time-cost measurement. The total cost of processing a match is given by the following equation:

$$Total\_Cost = IO\_Cost + CPU\_Cost \qquad (12)$$

where *IO_Cost* is the cost of performing disk I/Os and *CPU_Cost* is the cost for performing computation while retrieving the most similar contour from the library. In the experiment we only consider the *CPU_COST* and discard the *IO_Cost* as, compared to the CPU time, the time taken to read contour points from the library file can be ignored. Table 3 shows the time cost of three algorithms, according to different sets of input satellite images. Time evaluation is not stable but it can indicate a trend. The results show a trend towards the time warping distance measure being computationally faster than other two algorithms.

Table 3: Computational costs of three algorithms

	Input Image	Elastic Matching Model	Weighted Hausdorff Distance	Time Warping Distance
Average Time Cost (seconds)	Dvorak Template	49.19	43.09	37.9
	Other Satellite Images	113.797	83.375	86.28

Moreover, we also can prove this result by analyzing the computational costs of three algorithms. Suppose that the input contour has m points and the template contour has n points, Table 4 shows the computational complexities, which supports our approach.

Table 4: Computational complexities for three approaches

Algorithm	**Elastic Matching Model**	**Weighted Hausdorff Distance**	**Time Warping Distance**
Computation Complexity	$O(m^2n^2+m^2+n^2)$	$O(1.5m^2n)$	$O(m^2n)$

5. Conclusion and Future Work

In this paper we have presented a two-layer prototype of a system for measuring the similarity of two tropical cyclone shapes. By integrating into our approach an algorithm for finding the optimal time warping path, we have been able to determine the approximate distance between two angles found among the contour points of the cyclone shapes. The effect and efficiency of this system have been evaluated with particular attention to accuracy and time-cost.

Future research efforts will be directed towards improving the matching module's efficiency and matching accuracy, with special emphasis on improving the algorithm for finding the optimal time warping path. We will also collect more satellite images to facilitate further evaluation of our proposed prototype. Our research into tropical cyclone forecasting will also be extended to include other issues such as trajectory prediction.

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